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Smart Money: The Forecasting Ability of CFTC Large Traders in Agricultural Futures Markets

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The forecasting content of the Commodity Futures Trading Commission's Commitments of Traders (COT) report is investigated. Bivariate Granger causality tests show very little evidence that traders' positions are useful in forecasting (leading) returns in 10 agricultural futures markets. However, there is substantial evidence that traders respond to price changes. In particular, noncommercial traders display a tendency for trend following. The other trader classifications display mixed styles, perhaps indicating those trader categories capture a variety of traders. The results generally do not support use of the COT data in predicting price movements in agricultural futures markets.

Key words: agricultural futures markets, commitments of traders, forecasting, prices

Introduction

The Commodity Futures Trading Commission's (CFTC) Commitments of Traders (COT) report highlights the aggregate futures positions held by reporting (large) traders, both commercial (hedgers) and noncommercial (speculators). Futures traders often view these data as akin to insider information about the positions of "smart money" traders and tout its usefulness in predicting price movements (e.g., Upperman, 2006; Briese, 2008). Discussion of trader positions has now become routine among market analysts who search for meaning within the numbers. This focus contrasts with the CFTC's intent that the report function as one component of its market monitoring and surveillance system (CFTC, 2008).

Academic studies in recent years show commodity futures portfolios can generate returns comparable to equities (e.g., Gorton and Rouwenhorst, 2006). As a result, the financial industry has developed products allowing institutions to invest in commodities through long-only index funds as well as easily traded commodities through exchange-traded funds and other structured products. The rapid growth in these nontraditional futures market participants has led to concerns that such trading has altered the price discovery process in traditional agricultural commodity markets (Morrison, 2004). Indeed, Domanski and Heath (2007) argue that the "financialisation" of commodity markets warrants additional study on the strategies, motivation, and the potential market impact of nontraditional traders.

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A limited number of studies examine the ability of large trader positions to predict returns in agricultural futures markets.[1] Kahn (1986) uses COT observations to mimic the positions of noncommercial traders in corn, soybeans, wheat, and oats futures markets. He finds that following noncommercial positions (upon release of the COT reports) does not generate statistically significant profits. Examining price behavior during the "market scandal" associated with the May 1925 wheat futures contract at the Chicago Board of Trade, Petzel (1981) reports that lagged position changes for three groups of speculators are not significantly related to price changes for the contract. In a 2001 study, Wang develops "sentiment" indicators based on COT positions in six actively traded agricultural futures markets and finds positions of noncommercial traders forecast price continuations, and positions of commercial traders forecast price reversals. More recently, Wang (2003) investigates a trading strategy based on large trader position changes in corn, soybeans, wheat, and sugar, and reports significant profits following noncommercial positions and reversing commercial positions. Using causal inference algorithms, Bryant, Bessler, and Haigh (2006) do not find evidence of trader positions from COT reports predicting returns in corn and live cattle futures markets. Finally, Gorton, Hayashi, and Rouwenhorst (2007) examine a large cross-section of commodity futures markets and find only a few markets with significant correlations between returns and lagged commercial positions.

The mixed findings in prior research may be due to several factors, including different measures of position size and varying sample periods. For example, Wang (2001) utilizes a sentiment index that normalizes positions by the previous three-year range of positions, while Gorton, Hayashi, and Rouwenhorst (2007) normalize positions by the current level of open interest. The disparity of results suggests empirical findings may be sensitive to alternative position measures.

The goal of this research is to explicitly examine the usefulness of COT data in predicting agricultural futures returns. In light of the evolving nature of speculative participants in futures markets and the attention paid in the industry to the positions held by trader groups, it is important to directly address the usefulness of these data in a forecasting framework. This study uses bivariate Granger causality to investigate lead-lag dynamics between trader positions and agricultural futures returns over a relatively long time period, 1995 through 2006. Weekly data on 10 grain and livestock futures markets are examined. Importantly, the sensitivity of estimation results to several position measures is tested. A variation of the basic Granger causality test is used to test for longer-horizon relationships between trader positions and returns. A Cumby-Modest test is employed to determine whether trader positions impact returns when extreme market positions are reached. Trading styles are also investigated via causality tests from returns to positions, revealing if CFTC traders are trend followers or adhere to value- or contrarian-type strategies.

The research results will be of interest to academics and market participants alike. Academic researchers will gain a more thorough understanding of relationships between agricultural futures price movements and positions of different types of traders. Traders, analysts, and other market participants will benefit from a rigorous analysis of the COT data. For

[1] A large literature has investigated "hedging pressure" effects and/or "risk premiums" using COT data (e.g., Chang, 1985). However, most papers in this literature estimate the *contemporaneous* correlation between futures returns and positions. A contemporaneous correlation does not necessarily imply a causal relationship, as it may simply reflect the response of traders to futures price movements and/or the common reaction of returns and positions to fundamental supply and demand factors (Petzel, 1981). One study (Yang, Bessler, and Fung, 2004) tests whether a co-integrating relationship exists between changes in total open interest and subsequent returns for 11 storable and nonstorable futures markets. No evidence is found whereby open interest drives futures returns.

example, participants may find that the COT data provide little insight as to future price direction, in which case their efforts may be more efficiently directed toward alternative approaches to predicting market trends.

Commitments of Traders Reports

The COT report provides a breakdown of each Tuesday's open interest for futures markets in which 20 or more traders hold positions equal to or above the reporting levels established by the CFTC.[2] The weekly reports for *Futures-Only Commitments of Traders* and for *Futures-and-Options-Combined Commitments of Traders* are released every Friday at 3:30 p.m. Eastern Standard Time.

Reports are available in both a short and long format. The short report shows open interest (aggregated across all outstanding contracts) by reportable and nonreportable positions. For reportable positions, additional data are provided for commercial and noncommercial holdings, spreading, changes from the previous report, percentage of open interest by category, and number of traders. The long report, in addition to the information in the short report, also groups the data by crop year, where appropriate, and shows the concentration of positions held by the largest four and eight traders.

Starting in early 2007, as a response to complaints by traditional traders about long-only index traders (CFTC, 2006a,b), the CFTC released supplemental reports that also break out the positions of index traders for agricultural markets. The release of this report offers historical data starting in 2006, and it largely confirms the presupposition that index traders are almost exclusively long-only traders. For example, in the corn futures market, index traders are 96% long and hold roughly 12% of the open interest. As expected, index traders seldom alter positions other than to roll contract months, resulting in virtually no variation in their directional position. Therefore, we focus here on the combined futures and delta-adjusted options positions held within the traditional CFTC classifications: commercial, noncommercial, and nonreporting traders.

Using the information in the short report, noncommercial open interest is divided into long, short, and spreading, whereas commercial and nonreporting open interest is simply divided into long or short. The following relation explains how the market's total open interest (TOI) is disaggregated:

$$(1) \qquad \underbrace{[NCL + NCS + 2(NCSP)] + [CL + CS]}_{\text{Reporting}} + \underbrace{[NRL + NRS]}_{\text{Nonreporting}} = 2(TOI),$$

where *NCL*, *NCS*, and *NCSP* are noncommercial long, short, and spreading positions, respectively. *CL* (*CS*) represent commercial long (short) positions, and *NRL* (*NRS*) are long (short) positions held by nonreporting traders. Reporting and nonreporting positions must sum to the market's total open interest (*TOI*), and the number of longs must equal the number of short positions.

Data on trader positions are collected for each Tuesday from 1995 through 2006, resulting in 616 observations. The COT data reflect traders' positions as of Tuesday's close, although for much of the sample these data are not released until Friday. Following previous studies (e.g., Bryant, Bessler, and Haigh, 2006), a matching set of log-relative futures returns,

[2] See Hieronymus (1971), McDonald and Freund (1983), and Fenton and Martinaitas (2005) for extensive discussions of the history and evolution of the COT report.

$R_t = \ln(p_t / p_{t-1})$, is calculated for nearby futures using Tuesday-to-Tuesday settlement prices. We make no assumptions about how or why traders' positions might change over the course of a week, and the data are organized whereby the collected prices are coincidental with the reported positions. Therefore, the empirical tests are purely for predictive value from the time the positions are actually held, and they are not conditioned on the public release date. Failure to find predictive value under this test design most certainly precludes the positions from having forecasting value after a delayed release.

Position Indicators

Prior research results have varied, potentially due to alternative measures of position size. De Roon, Nijman, and Veld (2000) use the "percent net long" (PNL), which measures the net position of the average trader in a CFTC classification. The PNL is calculated as long minus the short positions divided by their sum for each trader classification. For instance, the PNL for the reporting noncommercials is defined as follows:

$$\text{Noncommercial } PNL_t = \frac{NCL_t - NCS_t}{NCL_t + NCS_t}. \tag{2}$$

The PNL for each CFTC classification represents the net position held by the group normalized by its total size.

Wang's (2001) sentiment index, $SI_{i,t}$ is also calculated for each market and classification, i (noncommercial, commercial, nonreporting). Wang defines the net long position for each trader category, $S_{i,t}$, as the total long positions minus the total short positions for that category at time t. Wang then defines his sentiment index by normalizing the net long position by its range over the prior three years:

$$SI_{i,t} = \frac{S_{i,t} - \text{Min}(S_{i,t})}{\text{Max}(S_{i,t}) - \text{Min}(S_{i,t})}. \tag{3}$$

Note that each of the minimum and maximum functions is applied to the prior three years. Wang's sentiment index is essentially an oscillator bound in the range $(0, 1)$. A value of 0 indicates the net long position is at a three-year low, while a value of 1 occurs when the net long position or trader sentiment is at a three-year high.

Not surprisingly, the correlations between the PNL and SI measures are very high. For example, using the corn futures positions, the simple correlation coefficients between *PNL* and *SI* are 0.97, 0.95, and 0.88 for noncommercial, commercial, and nonreporting positions, respectively. Other potential position measures are also examined—such as simple net position, position changes, and using alternative look-back periods (other than three years) for calculating the SI. Again, the correlations are generally very high (around 0.90) across all of the alternative position measures.

The following empirical tests are conducted using both the PNL and SI measures of position size. The results do not differ materially based on the position measure; consequently, our focus is on the PNL measure. In the next section, we discuss how the PNL position measure is used to uncover statistical lead-lag relationships within the data using Granger causality (results using the SI measure are available from the authors upon request).

Empirical Methods

Hamilton (1994) suggests the direct, or bivariate, Granger test for examining the lead-lag or "causal" relationship between two series. Granger causality is a standard linear technique for determining whether one time series is useful in forecasting another. In our case, the two time-series variables used are futures returns and trader positions (PNL). The following models are estimated:

$$R_t = \alpha_t + \sum_{i=1}^{m} \gamma_i R_{t-i} + \sum_{j=1}^{n} \beta_j PNL_{t-j} + \varepsilon_t, \tag{4}$$

and

$$PNL_t = \phi_t + \sum_{i=1}^{n} \lambda_i PNL_{t-i} + \sum_{j=1}^{m} \theta_j R_{t-j} + \omega_t. \tag{5}$$

Each model is estimated for lag lengths of 1 to 12 weeks, and the lag structure of the most efficient model is selected by minimizing the Akaike information criterion (AIC). The models are estimated with OLS. If the residuals demonstrate serial correlation (Breusch-Godfrey Lagrange multiplier test), additional lags of the dependent variable are added until the null of no serial correlation cannot be rejected. We test for heteroskedasticity (White test), and robust standard errors are used to correct the standard errors when necessary.

From equation (4), a number of testable hypotheses emerge. In particular, the null hypothesis of interest is that traders' positions (PNL) cannot be used to predict (do not lead) market returns (H_0: $\beta_j = 0\ \forall\ j$). A rejection of this null hypothesis would provide direct evidence trader positions are indeed useful for forecasting market returns. In order to gauge the aggregate impact of trader positions, we also test the null hypothesis that

$$\sum_{j=1}^{n} \beta_j = 0,$$

which will reveal the cumulative directional impact of traders' positions on returns (if any). Finally, the full rationality (efficiency) in futures returns is tested ($\gamma_i = \beta_j = 0 \forall i, j$) as well as autocorrelation in returns ($\gamma_i = 0 \forall i$).

In equation (5) there are two null hypothesis of interest. First, do returns lead traders' positions, $\theta_j = 0 \forall j$? Second, what is the cumulative impact of past returns on traders' positions,

$$\sum_{j=1}^{n} \theta_j = 0?$$

If we reject $\theta_j = 0\ \forall\ j$ and find

$$\sum_{j=1}^{n} \theta_j > 0,$$

then the trader group may be classified as trend followers or "positive feedback" traders because they increase their long position after prices increase and vice versa. Conversely, traders who buck the trend may be called "negative feedback" traders or contrarians, where

$$\theta_j \neq 0 \ \forall\ j \quad \text{and} \quad \sum_{j=1}^{n} \theta_j < 0.$$

These traders tend to buy after price declines and sell after price rallies, essentially a counter-trend strategy or "value" strategy. The tests outlined for equations (4) and (5) provide the basis for the empirical tests which yield important insight with regard to the usefulness of the

COT data in predicting agricultural futures price movements and the trading "style" of each trader group.

The previous Granger causality tests are designed to detect the relationship, if any, between weekly positions and returns. Such tests may have low power to detect relationships over longer horizons (Summers, 1986). For example, trader positions or speculative monies may flow in "waves" that build slowly—pushing prices higher—and then fade slowly. In this scenario, horizons longer than a week may be necessary to capture the predictive component of large trader positions. Thus, we implement the long-horizon regression "fads" models of Jegadeesh (1991):

$$R_t = \alpha_t + \sum_{i=1}^{m} \gamma_i R_{t-i} + \beta \sum_{j=1}^{n} \frac{PNL_{t-j}}{n} + \varepsilon_t . \tag{6}$$

In essence, equation (6) is analogous to (5) except that instead of PNL entering the model at alternative lags, it enters the model as a moving average calculated over the most recent *n* observations. Jegadeesh shows that letting the independent variable enter the equation as an average over the most recent *n* observations provides the highest power against a fads-type alternative hypothesis using standard OLS estimation and testing procedures. If the estimated β is positive (negative), then it indicates a fads-style model where prices tend to increase (decrease) slowly over a relatively long time period after widespread buying. The "fads" stylization captured in (6) is consistent with the popular notion of speculative pressures creating a "bubble" in commodity prices.

It is also possible that traders' positions have a market impact only when they reach extreme levels. Again, this would be somewhat consistent with an investing fad or bubble that may reverse when the market reaches a "frenzy." To test this assertion, we follow the method proposed by Sanders, Boris, and Manfredo (2004) by defining an extreme position as the upper and lower 20th percentile of the prior three-year range. Let the variable $LO = 1$ if PNL is in the lower 20th percentile of its range from the prior three years, and = 0 otherwise. Similarly, the variable $HI = 1$ if PNL is in the upper 20th percentile of its three-year range, and = 0 otherwise.

The following OLS regression is then used to test the impact of extreme positions on market returns:

$$R_t = \alpha_0 + \alpha_1 HI_{t-1} + \alpha_2 LO_{t-1} + \varepsilon_t . \tag{7}$$

Equation (7) is a version of the market-timing test proposed by Cumby and Modest (1987). It is essentially a difference in means test. If the mean return conditioned on extremely short positions ($\alpha_0 + \alpha_2$) or extremely long positions ($\alpha_0 + \alpha_1$) is different from the unconditional mean (α_0), then extreme PNL positions are useful in forecasting market returns. In this specification, a negative (positive) α_1 and a positive (negative) α_2 is indicative of price reversals (continuation). By using the first three years of the data to define *HI* and *LO*, the sample size remaining for estimation is reduced to 459 weeks. As with the Granger causality tests, initial estimates of (7) are tested and corrected for heteroskedasticity and autocorrelation using the White and Newey-West estimators (Hamilton, 1994, p. 281).

Results

Trends in Positions

The data are first examined visually to reveal simple trends and characteristics. In this section, we concentrate on a major feed grain—corn, and a major livestock market—live cattle. The trends in these futures markets are generally representative of the agricultural futures markets included in the study. Figure 1 shows the total open interest (futures plus delta-adjusted options) for corn (panel A) and live cattle (panel B). Total open interest for corn is relatively steady between 500,000 and 700,000 contracts through mid-2003. Then, open interest increases steadily to over 2 million contracts in late 2006. Over the same period, live cattle open interest experienced a doubling from 300,000 to 600,000 contracts. Many market participants attribute this increase to greater overall speculative activity (e.g., O'Hara, 2006). However, as shown in figure 2, the COT trader classifications are unable to confirm (or deny) this conjecture. Indeed, over the same time period, the commercial corn positions (panel A) are relatively flat at 45%–50% of total open interest. But there is marked increase in noncommercial activity from roughly 30% of open interest to more than 35% of open positions. However, this increase comes mostly at the expense of nonreporting speculators, whose open interest declines from nearly 25% to below 15%. Similar trends are shown for live cattle (panel B), where commercial positions are relatively stable and the noncommercial position size increases at the expense of the nonreporting group. Since nonreporting traders are not classified as commercial or noncommercial, we do not know if there was a relative loss of commercial or speculative traders. Still, it is clear from figures 1 and 2 that the markets seem to have undergone some changes since 2003.

Traders and market analysts often cite COT positions as a cause of price moves or a reason to expect a "sell-off" or "rebound" in prices. Figure 3 reveals an apparent relationship between corn futures prices and the PNL for noncommercial corn traders over 1998–2006. For instance, in panel A, a high corn price (325 cents per bushel) in early 2004 coincided with noncommercial traders being over 40% net long. The contemporaneous correlation between noncommercial PNL and corn price levels, 0.62, is in fact relatively high. Yet, as Petzel (1981), Sanders, Boris, and Manfredo (2004), and Gorton, Hayashi, and Rouwenhorst (2007) point out, this type of evidence can be misleading. High contemporaneous correlations do not necessarily imply a causal relationship since the correlation may simply reflect the response of traders to futures price movements and/or the common reaction of futures prices and positions to fundamental supply and demand factors. In the following section, the "smart money" view of COT report data is subjected to a rigorous test for predictive content.

Do Positions Lead Returns?

Equation (4) is estimated to test if trader positions are indeed useful in forecasting returns at a weekly horizon. In particular, a rejection of $\beta_j = 0 \; \forall \; j$ would provide some evidence that the importance placed on the COT data by the trading industry is well-founded. The *p*-values (*F*-test) for this and the other null hypotheses of interest are presented in tables 1, 2, and 3 for the noncommercial, commercial, and nonreporting trader groups, respectively.

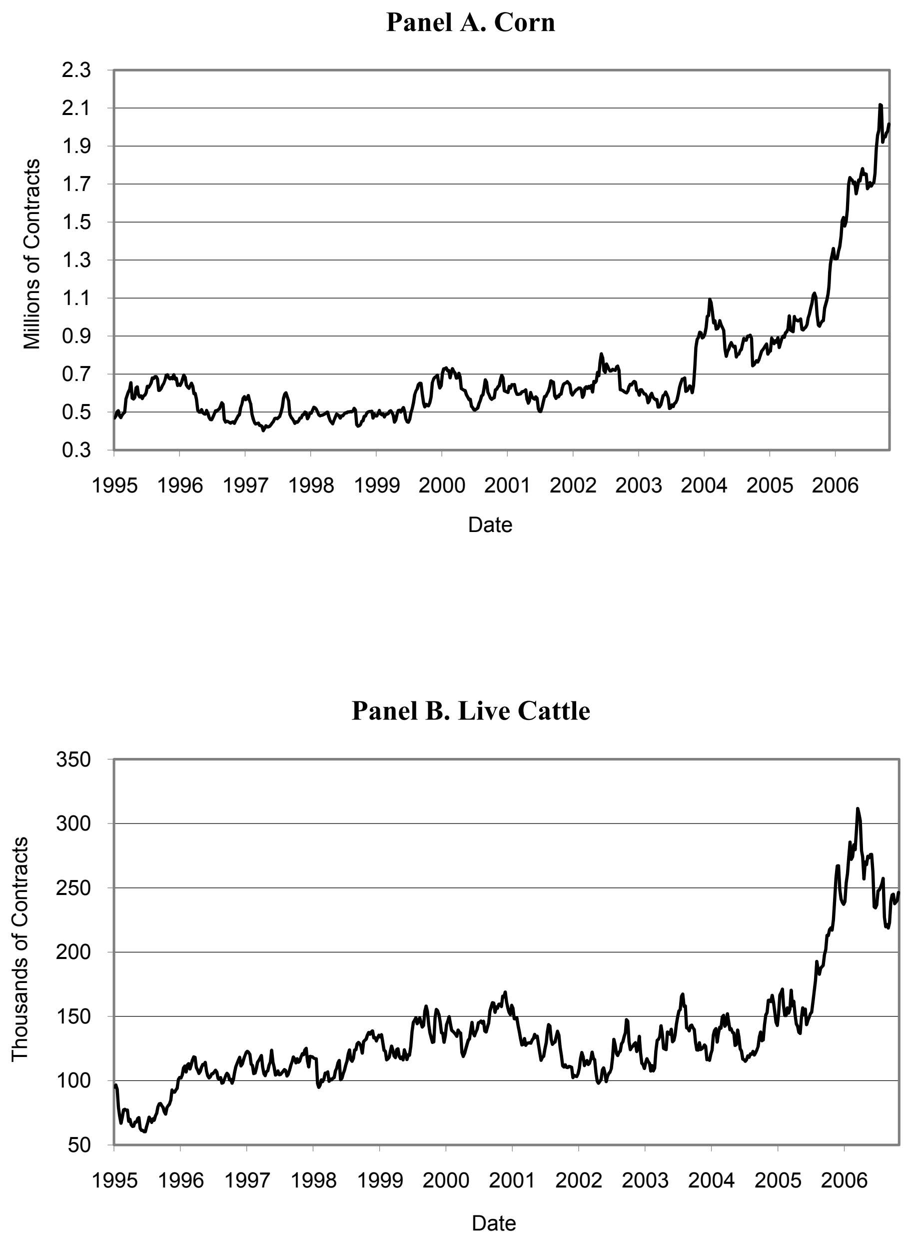
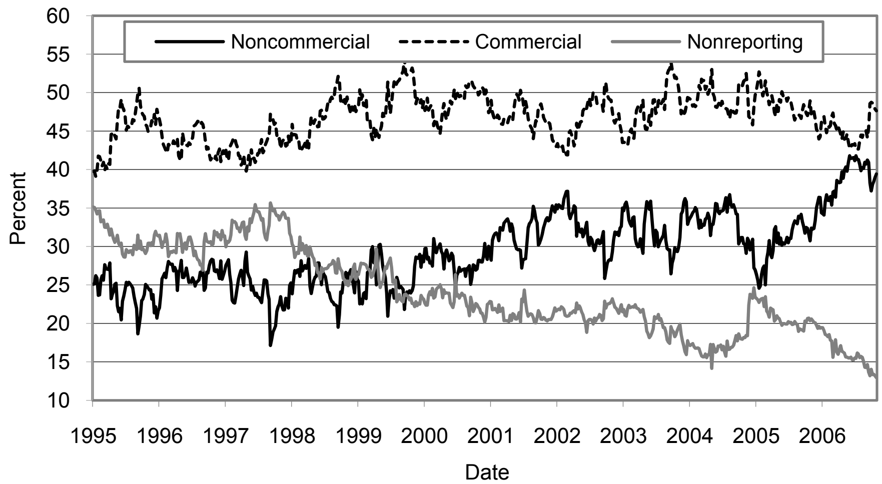


Figure 1. Combined futures and options open interest for two commodity markets, 1995–2006

Panel A. Corn



Panel B. Live Cattle

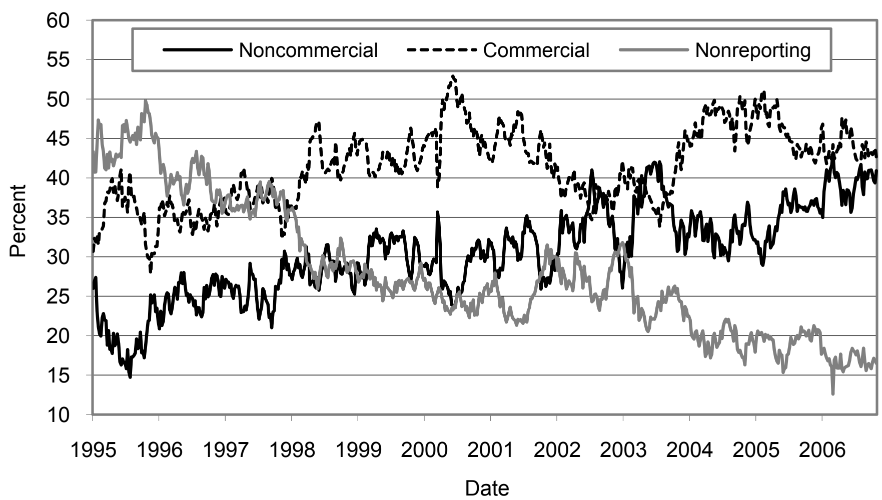
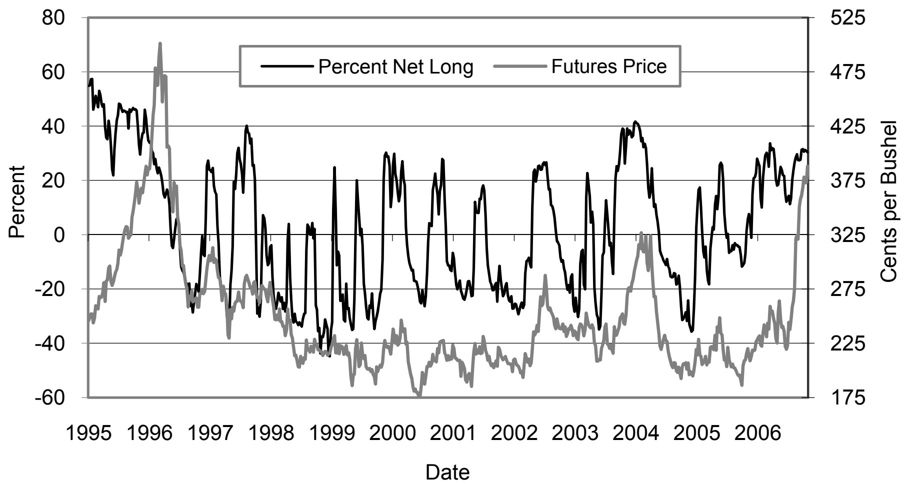


Figure 2. Percent of open interest by trader category for two commodity markets, 1995–2006

Panel A. Corn



Panel B. Live Cattle

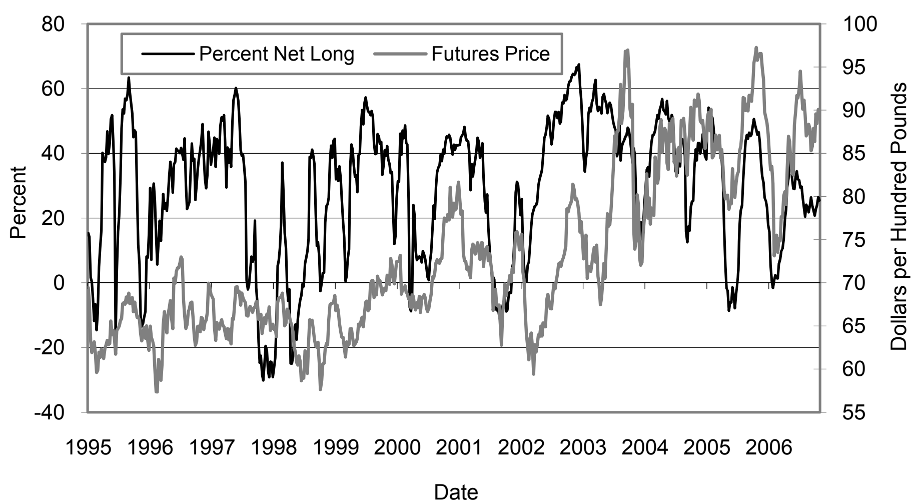


Figure 3. Noncommercial percent net long and futures prices for two commodity markets, 1995–2006

Table 1. Granger Causality Test Results for CFTC Noncommercial Traders Category (Null: *Positions do not lead returns, 1995–2006*)

		p-Values for Hypothesis Tests				
Market	*m*, *n*	$\beta_j = 0 \ \forall \ j$	$\sum \beta_j = 0$	$\gamma_i = 0 \ \forall \ i$	$\gamma_i = \beta_j = 0 \ \forall \ i, j$	Direction ($\sum \beta_j \times 10^2$)
Wheat CBOT	1, 2	0.177	0.649	0.035	0.156	−5.261
Wheat KCBOT	1, 6	0.237	0.382	0.299	0.319	7.462
Wheat MGEX	1, 1	0.151	0.151	0.896	0.345	0.004
Corn	4, 1	0.789	0.789	0.062	0.108	3.675
Soybeans	1, 1	0.047	0.047	0.877	0.070	−6.128
Soybean Oil	1, 1	0.300	0.300	0.375	0.552	5.420
Soybean Meal	1, 1	0.929	0.929	0.687	0.921	0.000
Lean Hogs	6, 1	0.338	0.338	0.122	0.145	0.000
Live Cattle	11, 1	0.826	0.826	0.000	0.000	−0.001
Feeder Cattle	2, 1	0.160	0.160	0.025	0.042	−0.005

Note: Estimated using text equation (4): $R_t = \alpha_t + \sum_{i=1}^{m} \gamma_i R_{t-i} + \sum_{j=1}^{n} \beta_j PNL_{t-j} + \varepsilon_t$.

In table 1, the null hypothesis that noncommercial positions (PNL) lead or forecast market returns is rejected at the 5% level only in soybeans (*p*-value = 0.047). In eight of the model specifications, lagged position values enter the equation at just a single lag ($n = 1$). In those models with more than a single lag, the null hypothesis ($\beta_j = 0 \ \forall \ j$) is still not rejected, and the cumulative position impact,

$$\sum_{j=1}^{n} \beta_j ,$$

also is not statistically different from zero. Collectively, there is little evidence that noncommercial positions are systematically useful in predicting returns. Interestingly, however, full rationality in futures returns $(\gamma_i = \beta_j = 0 \forall i, j)$ is rejected at the 5% level in two markets, mostly due to a low-order autocorrelation in returns $(\gamma_i = 0 \forall i)$.

The null hypothesis that commercial trader positions do not lead futures returns (table 2) is rejected at the 5% level in CBOT wheat, KCBOT wheat, and lean hogs. Thus, in 3 of the 10 markets, there is some evidence that commercial traders' positions are useful in forecasting returns. In CBOT wheat, we reject

$$\sum_{j=1}^{n} \beta_j = 0$$

and find that the cumulative directional impact is negative, suggesting commercials increase long (short) positions prior to price declines (increases). In KCBOT wheat and lean hogs, the aggregate impact is not statistically different from zero, suggesting an unusual directional impact with some lagged β coefficients positive and others negative. This evidence is far from overwhelming, and the mixed nature of the directional impacts makes any systematic impact appear unlikely. Again, it is worth noting that full rationality in futures returns ($\gamma_i = \beta_j = 0 \ \forall \ i, j$) is rejected at the 5% level in six markets, once more primarily due to a low-order autocorrelation in returns ($\gamma_i = 0 \ \forall \ i$).

Table 2. Granger Causality Test Results for CFTC Commercial Traders Category (Null: *Positions do not lead returns, 1995–2006*)

		p-Values for Hypothesis Tests				
Market	*m*, *n*	$\beta_j = 0\ \forall\ j$	$\sum \beta_j = 0$	$\gamma_i = 0\ \forall\ i$	$\gamma_i = \beta_j = 0\ \forall\ i, j$	Direction ($\sum \beta_j \times 10^2$)
Wheat CBOT	1, 2	0.007	0.041	0.068	0.018	−0.021
Wheat KCBOT	4, 6	0.030	0.076	0.054	0.005	−15.175
Wheat MGEX	1, 1	0.628	0.628	0.524	0.793	3.524
Corn	4, 2	0.351	0.617	0.009	0.030	4.308
Soybeans	1, 1	0.829	0.829	0.611	0.827	−0.002
Soybean Oil	1, 1	0.235	0.235	0.315	0.479	6.096
Soybean Meal	1, 1	0.702	0.702	0.437	0.725	−1.057
Lean Hogs	5, 7	0.049	0.872	0.086	0.023	−0.000
Live Cattle	11, 1	0.748	0.748	0.000	0.000	−0.003
Feeder Cattle	5, 1	0.095	0.095	0.007	0.007	−0.007

Note: Estimated using text equation (4): $R_t = \alpha_t + \sum_{i=1}^{m} \gamma_i R_{t-i} + \sum_{j=1}^{n} \beta_j PNL_{t-j} + \varepsilon_t$.

Table 3. Granger Causality Test Results for CFTC Nonreporting Traders Category (Null: *Positions do not lead returns, 1995–2006*)

		p-Values for Hypothesis Tests				
Market	*m*, *n*	$\beta_j = 0\ \forall\ j$	$\sum \beta_j = 0$	$\gamma_i = 0\ \forall\ i$	$\gamma_i = \beta_j = 0\ \forall\ i, j$	Direction ($\sum \beta_j \times 10^2$)
Wheat CBOT	1,1	0.539	0.539	0.328	0.584	−1.939
Wheat KCBOT	1,1	0.707	0.707	0.232	0.487	−0.700
Wheat MGEX	1,1	0.764	0.764	0.619	0.862	3.262
Corn	4,1	0.333	0.333	0.025	0.041	−0.015
Soybeans	1,1	0.778	0.778	0.531	0.674	−0.654
Soybean Oil	1,1	0.938	0.938	0.688	0.921	6.636
Soybean Meal	1,1	0.610	0.610	0.936	0.840	−0.001
Lean Hogs	5,1	0.080	0.080	0.106	0.045	−0.000
Live Cattle	11,1	0.477	0.477	0.000	0.000	−0.004
Feeder Cattle	5,1	0.226	0.226	0.012	0.010	0.005

Note: Estimated using text equation (4): $R_t = \alpha_t + \sum_{i=1}^{m} \gamma_i R_{t-i} + \sum_{j=1}^{n} \beta_j PNL_{t-j} + \varepsilon_t$.

As observed from table 3, the null hypothesis that nonreporting traders' positions do not lead returns is not rejected at the 5% level for any market. There is no substantive evidence that nonreporting traders' positions are useful for forecasting returns. This finding may not be surprising given the likely mixed motives of nonreporting traders, who may be speculators or hedgers. The results reported in table 3 again show evidence of low-order autocorrelation in returns.

Overall, the results do not support widespread causality from trader positions to returns. In the few markets where causality is documented—commercial traders' positions in the lean hogs, CBOT, and KCBOT wheat markets—the direction of the causality is mixed. The empirical results do point to one notable finding: weekly futures returns tend to show some low-order positive autocorrelation. This result is consistent with other research (e.g., Yang and Brorsen, 1994), and it suggests a failure to model lagged returns when investigating the COT data may result in misspecification errors.

Collectively, the results from tables 1, 2, and 3 reveal there is little systematic causality from traders' positions to returns within the agricultural futures markets examined. Given the noted shift in market participation in recent years (see figures 1 and 2), causal relationships may be masked by structural changes. Quandt likelihood-ratio tests for an unknown break point (Quandt, 1960; Andrews, 1993) do not reject the null hypothesis of "no break" at the 5% level for any of the models for noncommercial traders and for only a single market in both the commercial and nonreporting categories (results are available from the authors upon request). Hence, despite the rapid increase in open interest documented for these agricultural futures markets, there is little evidence that the relationship between traders' positions and returns (if any) has changed.

Long-horizon regressions [equation (6)] are specified by allowing $i = 1$ to 12 weeks, and $j = 1$ to 104 weeks, and then selecting the values that minimize the AIC. As an example, if $m = 1$ and $n = 1$, (6) reduces to a simple version of (5) with a single lag of returns (R) and positions (PNL). Alternatively, if $m = 2$ and $n = 4$ in (6), then the right-hand side includes two lags of returns (R) and the average PNL over the last four weeks. Allowing the potential specification for j to range from 1 to 104 weeks allows for the possibility that the impact of traders' positions accumulates over as much as two years before impacting market prices.

As in (4), a number of hypotheses can be tested using equation (6). However, here we focus on the most crucial null hypothesis: there is no long-horizon impact from trader positions to returns ($\beta = 0$). The specified lag selections and p-values for the hypothesis are presented in table 4. For the group of greatest interest among market participants—noncommercials or speculators—the null hypothesis is rejected one time at the 5% level in KCBOT wheat. For that market, the estimated β coefficient is positive (not shown) and the moving average of PNL is calculated over 101 weeks, suggesting that as large (long) speculative positions build, the market continues to see positive returns. Other than this single rejection, the overall results for the noncommercial category provide very little support for large speculators impacting market returns over long horizons.

The commercial and nonreporting categories likewise provide little statistical evidence for rejecting the null hypothesis. In the commercial category, $\beta = 0$ is rejected twice at the 5% level in feeder cattle and MGEX wheat. The sign on the estimated β coefficient is negative in feeder cattle and positive in MGEX wheat (not shown). This inconsistency suggests the impact of trader positions (if any) is potentially quite complicated and differs across markets. For the nonreporting segment, the null hypothesis is rejected one time at the 5% level in CBOT wheat. Importantly, within each category, the markets rejecting the null are not the

Table 4. Long-Horizon Granger Causality Test Results for CFTC Traders Categories (Null: *Positions do not lead returns, 1995-2006*)

	Lag Selection and p-Values for Hypothesis Tests					
	Noncommercial		Commercial		Nonreporting	
Market	m, n	$\beta = 0$	m, n	$\beta = 0$	m, n	$\beta = 0$
Wheat CBOT	1, 1	0.465	1, 1	0.372	1, 1	0.033
Wheat KCBOT	1, 101	0.007	4, 1	0.401	1, 49	0.066
Wheat MGEX	1, 1	0.138	1, 104	0.004	1, 1	0.212
Corn	4, 81	0.282	4, 81	0.327	4, 1	0.904
Soybeans	1, 69	0.419	1, 75	0.342	1, 73	0.327
Soybean Oil	1, 104	0.150	1, 104	0.102	1, 12	0.318
Soybean Meal	1, 54	0.735	1, 94	0.490	1, 85	0.441
Lean Hogs	12, 104	0.428	12, 104	0.142	12, 56	0.090
Live Cattle	11, 40	0.135	11, 42	0.205	11, 1	0.340
Feeder Cattle	5, 83	0.319	5, 20	0.022	2, 4	0.077

Note: Estimated using text equation (6): $R_t = \alpha_t + \sum_{i=1}^{m} \gamma_i R_{t-i} + \beta \sum_{j=1}^{n} \frac{PNL_{t-j}}{n} + \varepsilon_t$.

same as the markets in which Granger causality is found (tables 1–3). The relative inconsistency of the results, along with the scarcity of rejection, further erodes any evidence that trader positions are useful in predicting futures market returns.

Despite this evidence, it is still possible that traders impact market returns when extreme market positions are reached. Equation (7) is used to test this hypothesis, and the estimated coefficients are presented in table 5.[3] A positive (negative) α_1 coefficient suggests price continuation (reversals), while a positive (negative) α_2 indicates reversals (continuation). In table 5, there are two rejections of the null hypothesis at the 5% level for noncommercial traders, CBOT wheat and soybean oil. Interestingly, these rejections suggest continuation when noncommercials' PNLs reach extreme values. For example, when the PNL is in the upper 20th percentile of the three-year range, wheat conditional returns tend to increase by 1.53% in the following week. Soybean oil shows similar continuation with a 0.81% decline in conditional returns following relatively short noncommercial positions. These results generally do not support the idea that noncommercial traders push prices away from fundamental values, only later to have prices reverse.

For the commercial trader category, rejections occur at the 5% level in two markets: CBOT wheat and MGEX wheat. CBOT wheat shows return reversals following extreme commercial position levels, while MGEX wheat shows continuation at high position levels. Notably, CBOT wheat also displayed some evidence of Granger causality in table 2. The nonreporting category has one rejection of the null hypothesis (5% level), also in CBOT wheat.

[3] Equation (7) was also estimated by specifying alternative lag lengths (i = 1 to 12) for HI_{t-i} and LO_{t-i} and choosing the lag structure that minimized the AIC. Only corn (for noncommercial positions) had a lag length other than 1,1, and the null hypothesis was not rejected in this case. Hence, the results of this alternative specification process are not materially different from those presented in table 5.

Table 5. Cumby-Modest Test (Null: *Extreme positions do not predict returns, 1995–2006*)

Market	Noncommercial Coeffic.		Commercial Coeffic.		Nonreporting Coeffic.	
	α_1	α_2	α_1	α_2	α_1	α_2
Wheat CBOT	0.0153	0.0035	−0.0013	0.0112	0.0106	−0.0024
	(0.0002) [a]	(0.3108)	(0.7110)	(0.0201)	(0.0090)	(0.5049)
Wheat KCBOT	0.0000	0.0045	0.0016	0.0009	−0.0037	−0.0040
	(0.9924)	(0.3069)	(0.6733)	(0.7854)	(0.3663)	(0.2248)
Wheat MGEX	0.0056	0.0026	0.0061	0.0033	0.0004	0.0040
	(0.1252)	(0.3620)	(0.0348)	(0.3674)	(0.9129)	(0.2343)
Corn	−0.0033	0.0020	0.0069	0.0049	−0.0016	0.0046
	(0.3838)	(0.6067)	(0.0798)	(0.1822)	(0.6996)	(0.1966)
Soybeans	0.0037	−0.0009	−0.0050	−0.0060	−0.0020	−0.0001
	(0.3102)	(0.7918)	(0.1429)	(0.1240)	(0.6397)	(0.9667)
Soybean Oil	−0.0049	−0.0081	−0.0047	−0.0048	−0.0005	−0.0009
	(0.1920)	(0.0460)	(0.2275)	(0.2326)	(0.9034)	(0.8041)
Soybean Meal	0.0024	0.0023	−0.0000	0.0017	−0.0017	−0.0025
	(0.5856)	(0.5630)	(0.9893)	(0.7221)	(0.6976)	(0.5371)
Lean Hogs	0.0008	−0.0019	0.00013	0.0008	−0.0069	0.0049
	(0.8720)	(0.6885)	(0.7835)	(0.8878)	(0.2130)	(0.2444)
Live Cattle	0.0001	−0.0031	0.0007	0.0034	−0.0039	−0.0006
	(0.9574)	(0.2830)	(0.7620)	(0.1772)	(0.3513)	(0.7476)
Feeder Cattle	0.0000	−0.0022	0.0002	0.0011	−0.0047	−0.0017
	(0.9928)	(0.3826)	(0.9389)	(0.6369)	(0.0857)	(0.4174)

Note: Estimated using text equation (7): $R_t = \alpha_0 + \alpha_1 HI_{t-1} + \alpha_2 LO_{t-1} + \varepsilon_t$.

[a] Numbers in parentheses are p-values for two-tailed t-test.

Overall, there is some modest evidence of price movement following extreme market positions. However, the directional impacts are varied across markets, trader categories, and with the market positions. Market impacts (if any) stemming from extreme positions do not appear to be systematic across agricultural futures markets.

In total, the evidence that traders' positions lead futures returns over weekly or longer-term horizons is limited. Indeed, there is almost no systematic evidence to indicate non-reporting traders' positions are useful for predicting market returns in a Granger sense. Likewise, for noncommercials, the null hypothesis of no Granger causality is rejected only sporadically across markets and position measures. The long-horizon tests generally do not find that trader positions impact returns. Where there are rejections, the directional impacts differ across the markets, complicating the interpretation. Likewise, return patterns following extreme trader positions are inconsistent at best. The overall lack of statistical evidence—along with the inconsistencies across methods and markets—does not support a pervasive tendency for large trader positions to impact futures market returns.

Do Returns Lead Positions?

It is important to understand the dynamics of traders' positions. For instance, behavioral finance theories suggest positive feedback traders may be market destabilizing (De Long et

Table 6. Granger Causality Test Results for CFTC Noncommercial Traders Category (Null: *Returns do not lead positions, 1995-2006*)

		p-Values for Hypothesis Tests		
Market	*n*, *m*	$\theta_j = 0\ \forall\ j$	$\sum \theta_j = 0$	Direction ($\sum \theta_j$)
Wheat CBOT	6, 2	0.000	0.000	−84.57
Wheat KCBOT	2, 1	0.000	0.000	94.67
Wheat MGEX	12, 2	0.000	0.000	159.38
Corn	5, 2	0.000	0.000	70.56
Soybeans	2, 10	0.021	0.035	58.29
Soybean Oil	10, 2	0.000	0.000	−122.56
Soybean Meal	2, 9	0.000	0.001	135.29
Lean Hogs	12, 2	0.000	0.000	104.85
Live Cattle	3, 2	0.000	0.000	139.35
Feeder Cattle	8, 1	0.000	0.000	−77.65

Note: Estimated using text equation (5): $PNL_t = \phi_t + \sum_{i=1}^{n} \lambda_i PNL_{t-i} + \sum_{j=1}^{m} \theta_j R_{t-j} + \omega_t$.

al., 1990). To reveal potential trading "styles" among trader groups, equation (5) is estimated with the focus on the null that returns do not lead positions ($\theta_j = 0\ \forall\ j$) and whether or not the cumulative directional impact is positive or negative, i.e.,

$$\sum_{j=1}^{n} \theta_j > 0 \quad \text{or} \quad \sum_{j=1}^{n} \theta_j < 0.$$

A positive directional impact is indicative of trend followers or "positive feedback" traders because they increase their long position after prices increase and vice versa. A negative directional impact suggests "negative feedback" traders or contrarian strategies.

The results from estimating equation (5) are presented in table 6 for the noncommercial classification. The null hypothesis that returns do not cause positions is rejected at the 5% level across all markets. There is a systematic and pervasive tendency for returns to lead positions. Moreover, the aggregate directional impact is statistically different from zero in all 10 markets at the 5% level, with 7 of those 10 markets clearly displaying positive feedback trading on the part of noncommercial traders,

$$\sum_{j=1}^{n} \theta_j > 0.$$

These results are consistent with the findings of most other researchers (e.g., Sanders, Irwin, and Leuthold, 2003; Rothig and Chiarella, 2007), suggesting noncommercial traders may be utilizing trend-following systems.

The results for commercial traders (table 7) reveal that the null hypothesis ($\theta_j = 0\ \forall\ j$) is rejected in 8 of 10 markets at the 5% level. The cumulative directional impact,

$$\sum_{j=1}^{n} \theta_j,$$

Table 7. Granger Causality Test Results for CFTC Commercial Traders Category (Null: *Returns do not lead positions, 1995–2006*)

Market	n, m	p-Values for Hypothesis Tests: $\theta_j = 0 \; \forall \; j$	$\sum \theta_j = 0$	Direction ($\sum \theta_j$)
Wheat CBOT	7, 1	0.000	0.000	36.15
Wheat KCBOT	2, 1	0.000	0.000	−24.66
Wheat MGEX	1, 4	0.000	0.039	−21.92
Corn	2, 5	0.044	0.127	−18.59
Soybeans	11, 1	0.222	0.222	−8.75
Soybean Oil	10, 1	0.000	0.000	42.49
Soybean Meal	1, 10	0.054	0.129	−29.41
Lean Hogs	12, 2	0.000	0.000	−40.81
Live Cattle	2, 3	0.000	0.000	−62.74
Feeder Cattle	5, 1	0.027	0.027	27.65

Note: Estimated using text equation (5): $PNL_t = \phi_t + \sum_{i=1}^{n} \lambda_i PNL_{t-i} + \sum_{j=1}^{m} \theta_j R_{t-j} + \omega_t$.

Table 8. Granger Causality Test Results for CFTC Nonreporting Traders Category (Null: *Returns do not lead positions, 1995–2006*)

Market	n, m	p-Values for Hypothesis Tests: $\theta_j = 0 \; \forall$ j	$\sum \theta_j = 0$	Direction ($\sum \theta_j$)
Wheat CBOT	5, 2	0.027	0.469	4.73
Wheat KCBOT	3, 1	0.067	0.067	9.39
Wheat MGEX	3, 1	0.851	0.851	1.30
Corn	1, 1	0.003	0.003	−10.77
Soybeans	1, 2	0.036	0.014	−13.45
Soybean Oil	5, 4	0.000	0.000	−115.99
Soybean Meal	3, 1	0.000	0.000	21.13
Lean Hogs	1, 6	0.160	0.653	4.09
Live Cattle	3, 1	0.039	0.039	−13.71
Feeder Cattle	2, 1	0.000	0.000	28.07

Note: Estimated using text equation (5): $PNL_t = \phi_t + \sum_{i=1}^{n} \lambda_i PNL_{t-i} + \sum_{j=1}^{m} \theta_j R_{t-j} + \omega_t$.

is statistically different from zero at the 5% level in 7 of 10 markets, of which four display a negative cumulative impact or "value" strategies. In total, 7 of the 10 directional indicators are negative, suggesting short hedgers are scale-up sellers and long hedgers are scale-down buyers. However, the directional evidence is not overwhelming toward either style. This finding may stem from a heterogeneous group of traders potentially captured in the comercial category.

Perhaps not surprisingly, the results for nonreporting traders also are mixed (table 8). The null hypothesis that returns do not lead positions is rejected in 8 of the 10 markets at the 5% level. The cumulative impact is different from zero in 7 out of 10 markets (5% level), with four of those showing a negative feedback style, somewhat consistent with the commercial group.

In total, the above results build a strong case that returns lead positions. While the general trading style of noncommercials can be tentatively classified as one of positive feedback strategies, the results for the commercial and nonreporting categories are more mixed, with no clearly dominant style within each group. These results may reflect that both the commercial and nonreporting categories are capturing a diverse group of traders, where the composition may change across markets (Ederington and Lee, 2002).

Conclusions

The goal of this research was to explicitly examine the usefulness of the Commodity Futures Trading Commission's (CFTC's) Commitments of Traders (COT) data in predicting agricultural futures returns. In light of the evolving nature of speculative participants in futures markets and the attention paid in the industry to the positions held by trader groups, it is important to directly address the usefulness of these data in a forecasting framework. Here, we used a standard bivariate Granger causality approach to investigate the lead-lag dynamics between traders' positions and returns in 10 agricultural futures markets. A variation of the Granger approach was used to test for long-horizon impact of trader positions. A Cumby-Modest test was employed to determine whether trader positions impact returns when extreme market positions are reached.

The empirical results suggest two primary findings. First, traders' positions do not show a systematic and pervasive tendency to lead returns. In particular, there is practically no ability to forecast market returns using either noncommercial or nonreporting positions. Over weekly horizons, there is some weak evidence that commercial positions lead returns in a few specific markets (i.e., lean hogs, CBOT, and KCBOT wheat); however, this is not a pervasive theme across markets. Long-horizon tests again showed very little and inconsistent support for trader positions impacting returns. Market impacts (if any) stemming from extreme positions do not appear to be systematic across agricultural futures markets.

Second, the results clearly demonstrate that positions follow returns. In particular, noncommercial traders increase long positions after prices increase, and they therefore appear to be trend followers. The directional findings for commercial traders and nonreporting traders are more varied, with some markets showing trend-following styles and others showing contrarian or value strategies. The mixed directional evidence may reflect a hodgepodge of speculators and hedgers captured in these categories.

The results of this study have practical ramifications for academic researchers and market participants alike. Academic researchers should take note of the strong case for trading styles documented in this work, in particular the trend-following displayed by noncommercial traders. Sanders, Irwin, and Leuthold (2003) document similar styles for market newsletter writers and advisors as captured in market sentiment indices. This suggests there may be groups of traders who systematically employ simplified trading or hedging rules. Based on behavioral finance theories (e.g., De Long et al., 1990), the existence of such traders can have implications for market behavior even though it was not captured by the methods specific to this study.

For practitioners, the usefulness of the COT data in forecasting returns is suspect. In particular, noncommercial, or "fund," positions provide virtually no forecasting information for returns in agricultural futures markets. Indeed, noncommercial positions are basically a linear extrapolation of past price changes, consistent with trend-following strategies. If the COT data provide any forecasting information, it is likely found in the commercial category and in isolated markets. Even in cases where some evidence exists, the direction of the impact is varied across horizons and markets. So, if it is possible to utilize COT data to anticipate market movements, it is unlikely to be through a simplistic and consistent rule across markets. Moreover, the delay from the time the positions are recorded on Tuesday to their release on Friday would further erode any predictive power. As an alternative approach, practitioners may want to mimic the trading style—e.g., trend-following—displayed by their preferred trader group.

Overall, the evidence for predictive power is rather weak. The presented results are consistent with those reported by Dale and Zyren (1996) who state, "… noncommercial traders follow price trends: they don't set them" (p. 23). Still, traders and market analysts frequently rely on the COT data, as these data are widely used in analyzing market activity. Thus, there is a seeming paradox between the predictive power of the COT data as presented in this research and its perceived (or real) usefulness to those in the industry. Perhaps the COT data simply provide market commentators with convenient talking points or justification for otherwise difficult-to-explain market movements. Alternatively, the COT data may indeed provide a glimpse of the "smart money" in a fashion not easily captured by standard empirics.

Finally, Streeter and Tomek (1992) argue that if speculator positions do impact returns, it is most likely to occur over time horizons much shorter than a week, the observation interval for published COT reports. Daily data on trader positions are used to create the weekly COT reports, but these disaggregated data have been made available to only a few researchers over the years (Hartzmark, 1987; Leuthold, Garcia, and Liu, 1994; Ederington and Lee, 2002). Given the important public debate underway about the impact of speculation in agricultural futures markets, regulators should strongly consider allowing more researchers access to the underlying daily data for COT reports.

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